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Probabilistic evaluation of vegetation drought likelihood and its implications to resilience across India

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ABSTRACT

Vegetation distribution and growth are significantly affected by changing climate conditions. Understanding the response of vegetation to hydroclimatic disturbances such as droughts is crucial in context of climate change. The sensitivity of terrestrial ecosystem to drought is difficult to measure because of problems related to drought quantification, variable response of vegetation types and changing climate-vegetation dynamics. Since, India is hugely dependent on its vegetation and cropland, identifying the impact of droughts on vegetation is essential. In this study, we estimate the likelihood of vegetation droughts across India in changing scenarios of temperature, precipitation and soil moisture content. We also study the resilience of vegetation cover to disturbances induced by a dry condition. From the investigation, it is observed that at least half the area of 16 out of 24 major river basins is facing high chances of vegetation droughts due to lowered soil moisture levels. The croplands are most likely to be affected by drought, which is of paramount concern for country's food security. Further investigation suggests that at least one-third area of 18 river basins is non-resilient to vegetation droughts. Moreover, > 50% of each vegetation type is non-resilient, which points out the fragility of country's terrestrial ecosystems. This study facilitates the understanding of vegetation drought hotspot regions, factors risking the terrestrial ecosystem and their ability to withstand such conditions. These findings provide useful insights for policy makers to develop effective strategies for vegetation drought mitigation and sustainable ecosystem management.

1. Introduction

Climate change is one of the main factors which disturbs vegetation growth and activity (Flannigan et al., 2000; Hinzman et al., 2005; Piao and Fang, 2003; Schimel et al., 2001). Climate warming may result in intensified hydrological cycle which can further give rise to more drought events (Dai, 2011; Huntington, 2006). Dai (2013) from the analysis of soil-moisture, drought indices and precipitation-evaporation patterns suggested that the chances of drought have increased in this century. Drought, which arises because of the long-term deficit in water availability, is an integral part of vegetation-atmosphere interaction. A prolonged drought period influences the feedback processes between soil and atmosphere resulting in decline of soil moisture content. Plants depend solely on soil moisture to fetch required water for photosynthesis, which further controls the stem-water dynamics, stomatal regulation and transpiration losses (Bréda and Granier, 1996). Moreover, investigation of climate impact on vegetation growth needs the understanding of soil moisture conditions and variability associated with it (Brunner et al., 2009). Long term precipitation deficit and high temperature cause increase in atmospheric water demand which results in depletion of moisture content in the root zone depth. This has potential of severly impacting the vegetation growth and activity, specially considering the fact that climate warming will result in an increase in precipitation and evapotranspiration, leading to intensified hydrological cycles (Huntington, 2006). Since, there is a great amount of variability associated with warming magntitude and pattern of warming, the quantity of increase or decrease in evapotranspiration also induces the alteration in soil moisture availability making the system furhter complex (Koster et al., 2006; Mueller and Seneviratne, 2012; Seneviratne et al., 2010). An important study by Allen et al. (2010) identified the increased risks of vegetation mortality due to change in soil moisture droughts and rising temperature. Several other studies can be referred those underline the detrimental impact of drought on vegetation distribution and growth (Peters et al., 2002; Vicente-Serrano et al., 2013; Wan et al., 2010). There are significant problems related to assessment of droughts its impact on vegetation. Quantification of drought characteristics is difficult as we primarily identify droughts by its impact on different systems. Moreover, it is

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intricate to identify the exact time when drought starts and ends (Nagarajan, 2009). The complex nature of drought introduces various elements of uncertainties to identify the impact on different vegetation types (Vicente-Serrano et al., 2012). For instance, Zhang et al. (2017) in their work suggested that it is important to incorporate the duration, distribution, trends and severity as well as their complex interactions. Further, the assessment is constrained as the ecosystem response to drought disturbances is a function of both vegetation type and climate conditions (Wu and Chen, 2013). Sharma and Goyal (2017), in a comprehensive study of impact of hydroclimatic disturbance on ecosystem resilience found that every vegetation type, climate zone and river basin has a unique response to the climate conditions which should be considered while studying the ecosystem-climate interactions.

Normalized difference vegetation index (NDVI) is the most frequently used vegetation index to assess the vegetation condition. The significant relationship between NDVI and climate variables has been utilized to understand the influence of climate on vegetation. Li et al. (2010) suggested that significant correlation exist between NDVI and different eco-climatic parameters for different vegetation types. Assessment of NDVI and climate variable may provide useful insights in the investigation of key factors which control changes in vegetation ecosystems (Braswell et al., 1997; Okin and Dong, 2018; Potter and Brooks, 1998; Zhao et al., 2018). However, the mechanism of vegetation response to climate disturbances such as droughts is still unclear. Moreover, most of the studies about vegetation pattern and drought are focused around analyzing the characteristic of individual variables or indices. In relation to the vegetation-drought conditions, NDVI at times, has been directly compared to precipitation or the drought indices (Mohler et al., 1986; Tucker, 1989; Tucker and Choudhury, 1987). Later, Vegetation Condition Index (VCI), Standardized Vegetation Index (SVI) and Vegetation Drought Response Index (VegDRI) were derived to understand the vegetation drought dynamics (Brown et al., 2008; Peters et al., 2002; Sahoo et al., 2015). The employability of these NDVI derived vegetation indices has been shown by many studies since the 1990's (Kogan, 1995; Kogan, 1990; Quiring and Ganesh, 2010; Zambrano et al., 2016). However, like any other drought related indices, vegetation indices are also sensitive to environmental conditions which can result in misinterpretation of vegetation response to droughts. They provide the robust description of vegetation condition, but it is often inefficient in understanding the mechanism of drought related vegetation stress (Brown et al., 2008). Moreover, drought properties have also been examined by univariate analysis of climate variables (Cancelliere and Salas, 2004; Grimaldi and Serinaldi, 2006). Since, the significant correlation between climate variables is not captured during univariate analysis and many researchers have recommended the use of joint distribution to describe the drought characteristics (Chen et al., 2012; Huang et al., 2014; Kao and Govindaraju, 2010). Given the fact that vegetation drought is further complex phenomenon, modelling the vegetation-climate interaction from joint likelihood point of view is more suitable. A more robust idea would be to adopt a multivariate approach for examining the interrelationship of NDVI and climate variable and then derive the joint probabilistic behavior to explain the vegetation-climate interaction. However, generally used multivariate distributions are the extensions of univariate ones and suffer from many limitations (Salvadori and De Michele, 2004), for example, shortcoming of using bivariate distributions is related to complex mathematical derivations required for fitting parameters from generated or observed data (Shiau, 2006). Further, the marginal distribution need to be same, or must be modified to become normally distributed or independent which compromises the accuracy of the approach. These methods also assume that involved variables are based on the assumption of stationarity which does not hold good in the context of climate studies and must be incorporated while studying extreme hydrologic events (Bracken et al., 2018; Das and Umamahesh, 2017; Khaliq et al., 2006). These limitations can be tackled by incorporating the copula approach in multivariate analysis. Copula is an effective tool to model multivariate distribution among random variables and is independent of individual probabilistic specifications (Sklar, 1959). This method is advantageous in modelling the joint distributions as the dependence structure is modeled independently of the marginal distributions. There are several studies which support the idea that copulas provide a robust methodology for studying hydro-climatic events which can be referred for detailed information (Bracken et al., 2018; Goswami et al., 2018; De Michele and Salvadori, 2003; Favre et al., 2004a; Gomez et al., 2017; Grimaldi and Serinaldi, 2006; Kao and Govindaraju, 2010; Zhang et al., 2013). The copula based probabilistic approach enables to investigate the vegetation-drought dynamics and its occurrence through joint probability distributions. However, not only the occurrence, but ability to recover from the impact also plays an important role in governing the vegetation response. In this sense, the assessment of resilience is crucial in addressing the disturbance driven processes like vegetation droughts.

The basic idea behind estimating the resilience is to understand the ability of an ecosystem to absorb alterations in its state and recover from it (Holling, 1973). In the context of this study, resilience has been viewed as the strength of an ecosystem to return to equilibrium position after a drought disturbance. As discussed, droughts severely alter the hydrological equations and leading to alterations in water balance equations. One of the most important drivers behind existing vegetation is the water availability and vice-versa (Stephenson, 1990; Williams et al., 2012). The water balance equation between land and atmosphere govern the variation of forest biomass (Stegen et al., 2011). The amount of photosynthesizing biomass at different temporal and spatial scale can be ideally measured by NDVI. Earlier, remote sensing observations have been utilized to understand the ecological resilience. Cui et al. (2013) quantified the vegetation change and residence in semi-arid ecosystems and found that recovery after a dry condition during 1980s occurred by 1990s and 2000s. Further, a resilience indicator was developed based on NDVI, drought indicators and temperature anomalies (De Keersmaecker et al., 2015). The impact of droughts on growth resilience of forests in the Northern Hemisphere was quantified based on how the forest resist drought and recover after the event (Gazol et al., 2017). In a recent study, forest resilience to drought was analyzed based on tree ring width data and NDVI for a wide range of forests in Spain and it was found that forest resilience differs across biomes (Gazol et al., 2018). Studies related to resilience of vegetation in the Indian context are mostly confined to agricultural domain. A study by Duncan et al. (2017) shows that farmers in Indian states have suffered due to poorly resilient rice crops. Further, in a recent study, nutritional yield and climate-resilience of cereal crop in Central India was also discussed (DeFries et al., 2016). This study utilizes the changes in NDVI in a resilience framework for studying the impact of drought over all types of vegetation covers on a pan-India scale. Following the definition of resilience, we assumed that a resilient ecosystem will be least disturbed by a drought scenario and will not show much variation in its NDVI value as compared to the temporal mean NDVI (1982–2010) value. We quantified the resilience by comparing the NDVI value of driest year to the mean NDVI value and related it to different scales.

Here, we present a novel study, integrating climate data (precipitation, temperature and soil moisture content) and remote sensing observations (NDVI) by a bivariate copula-based approach to quantify the likelihood of vegetation droughts in India. To the best of authors' knowledge, the present investigation will be the first copula-based bivariate approach to assess the vegetation-dynamics of whole country. This study aims to know (i) the extent of vegetation cover likely to be hit by vegetation droughts in changing climate scenario; (ii) the vulnerability associated with vegetation droughts in context of different spatial, i.e. river basin and vegetation type and temporal scales i.e. seasonal and annual time period; (iii) the most influencing climate factor inducing vegetation droughts, and (iv) the resilience of vegetation cover of the country to dry conditions to present a broader picture

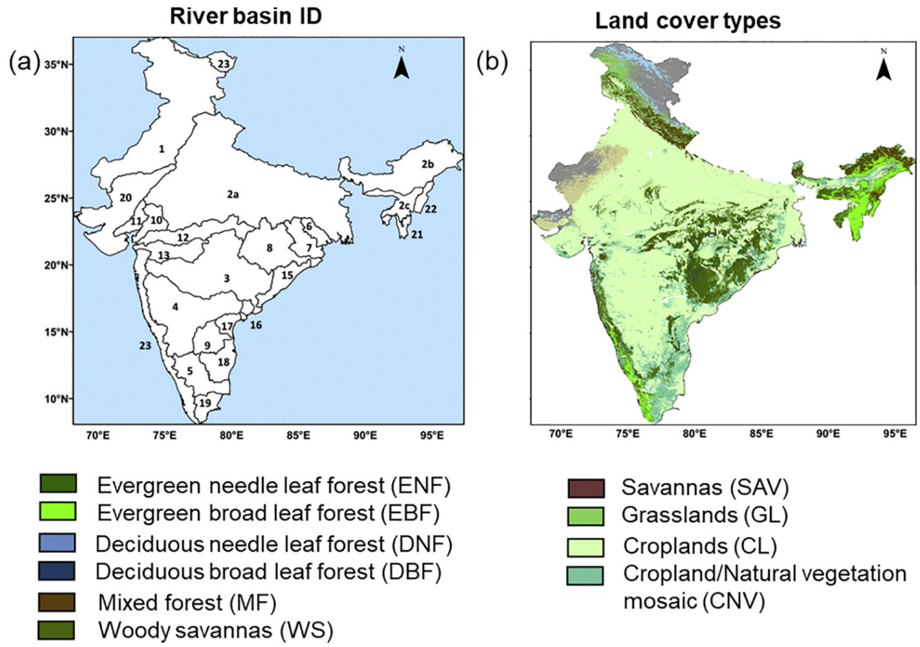

Fig. 1. (a) River basins and (b) vegetation types considered in the study.

of their ability to resist and withstand drought risks.

2. Materials and methods

2.1. River basins of India and vegetation types

Many major rivers basins across the globe have witnessed changes in their natural ability to absorb the impacts of climate change. Changes in climate conditions lead to alteration in water balance equation of a river basin leading to changes in rainfall-runoff relationships. The hydrological variables, which depend on physical and geological characteristics of a river basin, govern the response of vegetation to climate disturbances. An analysis, which could characterize river basins on the basis of its vulnerability to vegetation drought risks, will prove to be useful for the decision makers to formulate mitigation policies. For this study, 24 major river basins of India were demarcated according to the India-WRIS (2014) classification to quantify the likelihood of vegetation droughts and their ability to absorb and recover from such disturbances. Basin codes and their corresponding details are presented in Fig. 1 and Table 1. Moreover, India's vegetation significantly varies on spatial and temporal scale, thus, the results were also related to major vegetation types in the country. We studied different land cover classifications, which is based on 10 years (2001 – 2010) collection of 5.1 MCD12Q1 cover type data of USGS Land Cover Institute (LCI), https://landcover.usgs.gov/global_climatology.php (Broxton et al., 2014). The details about different vegetation types considered in this study are shown in Fig. 1. Among the considered land cover classes, croplands (CL) is one of the most dominant vegetation types covering > 50% of the total area of the country (Yue et al., 2014). Major forest cover types are deciduous forests (DBF and DNF) which are known to follow season pattern of leaf-on and leaf-off periods. These forest types are found irregularly in all parts of the country except Rajasthan and Himalayan region (Reddy et al., 2015). The evergreen forests (ENF and EBF), found mainly in the Deccan and coastal plains with limited spread over lower slopes of North East, Aravalli and Western Ghats are known to remain green most of the times(Joshi et al., 2011).

2.2. Climate data and NDVI

For the present study, gridded climate data of mean monthly temperature, precipitation and soil moisture content for the period of 1982–201 were analyzed. The precipitation data has been extracted from of a high spatial resolution ($0.25^{\circ} \times 0.25^{\circ}$) data set IMD4, covering a period of 110 years (1901–2010) (Pai et al., 2014). These datasets have been prepared from daily rainfall records of a dense network of 6955rain gauge stations in India. As declared by Indian Meteorological Department (IMD), the gridded data set was developed not only after making quality control of basic rain gauge stations, but also was checked and verified for similarity with other existing gridded data sets before release. Precipitation data from the IMD source is known to capture the spatial variability of Indian monsoon more efficiently than other similar sources and Mishra et al. (2014) recommended the use of these data sets for drought analysis as these are more realistic in nature. Temperature data for the period of 1982–2010 was also obtained from IMD, which was developed using Shepard's angular distance method from 395observational station in the country (Dosio et al., 2017; Srivastava et al., 2009). The error associated with the data set was estimated using cross validation method and found to be $< 0.5^{\circ}C$ and was also compared with other high resolution data sets for the country (Srivastava et al., 2009). The soil moisture data, was extracted from the Climate Prediction Centre (CPC) soil moisture data product developed by Earth System Research Laboratory of National Oceanic Atmospheric Administration (ESRL-NOAA) (http://www.esrl.noaa.gov/psd/data/gridded/data.cpcsoil.html) .The data validation and its application in various sectors suggest that both interannual and annual variability of soil moisture is well captured and produce good results in soil-climate interaction studies (Fan and van den Dool, 2004; Herbener, 2017; Koster et al., 2016; Prasad et al., 2006). NDVI data, which is a good indicator for analyzing vegetation productivity was extracted from Global Inventory Modelling and Mapping Studies (GIMMS) (http://ecocast.arc.nasa.gov/data/pub/gimms/3g/) with a spatial and temporal scale of 8 × 8 km and 15 days respectively. This data set is considered as ideal to monitor the changes in vegetation productivity and has been widely used to analyze the relationship between climate and vegetation interaction (Tan and Gan, 2016; Zhang et al., 2017; Zhao et al., 2018). The GIMMS data set from the Advanced Very High Resolution Radiometer (NOAA-AVHRR) sensor has been corrected for orbital drift errors and vegetation change (Liu et al., 2016a). This dataset is also among the longest available continuous remotely sensed vegetation data set which makes it suitable to be used in the study.

Table 1
Area highly likely to be affected by vegetation drought on annual scale in stressed climate scenario (n ≤ 20%) for different river basins obtained from different sets of NDVI and climate variables. Refer Fig. 2 for basin locations.

Id	Basin	NDVI-Soil moisture content		NDVI-precipitation		NDVI-temperature	
		Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)
1	Indus	37.51	171,895.82	24.04	110,170.58	14.02	64,261.79
2a	Ganga	23.32	186,076.66	7.03	56,089.53	14.90	118,933.74
2b	Brahmaputra	3.13	5922.05	0.35	662.22	21.54	40,794.74
2c	Barak	0.00	0.00	0.00	0.00	1.55	2932.01
3	Godavari	42.08	119,257.43	18.50	52,433.48	5.09	14,439.88
4	Krishna	57.42	134,991.39	40.82	95,957.80	1.74	4096.63
5	Cauveri	82.72	64,642.43	16.08	12,568.52	0.00	0.00
6	Subarnarekha	29.75	7091.77	2.19	522.08	0.00	0.00
7	BB*[1]	33.91	17,066.22	0.00	0.00	3.38	1702.14
8	Mahanadi	3.42	4321.61	1.30	1644.92	31.82	40,248.57
9	Pennar	96.72	44,837.21	46.11	21,372.31	0.00	0.00
10	Mahi	90.74	34,249.38	37.51	14,158.35	0.00	0.00
11	Sabarmati	86.32	24,579.23	45.56	12,972.75	0.00	0.00
12	Narmada	33.99	29,488.67	13.51	11,720.72	27.25	23,640.12
13	Tapi	82.76	52,067.54	18.87	11,871.46	5.09	3203.90
15	EFRMGB*[2]	62.57	29,417.98	16.20	7615.70	4.02	1888.94
16	EFRGKB*[3]	73.20	6301.29	15.38	1324.44	61.54	5297.76
17	EFRKPB*[4]	98.37	23,451.99	44.45	10,596.10	0.00	0.00
18	EFRPCB*[5]	85.64	45,937.77	9.60	5151.57	0.00	0.00
19	EFRSCB*[6]	14.45	4305.51	6.67	1987.74	0.00	0.00
20	Luni	91.75	169,525.94	81.56	150,691.94	0.00	0.00
21	MRBB*[7]	3.44	501.21	0.00	0.00	0.00	0.00
22	MRMB*[8]	0.00	0.00	0.00	0.00	33.82	4927.90
23	WG*[9]	29.74	30,528.05	5.43	5574.60	0.65	662.22

*[1] Brahmani and Baitarni Basin *[2] East flowing rivers between Mahanadi and Godavari Basin, *[3] East flowing rivers between Godavari and Krishna Basin, *[4] East flowing rivers between Krishna and Pennar Basin, *[5] East flowing rivers between Pennar and Cauvery Basin, *[6] East flowing rivers South of Cauvery Basin, *[7] Minor rivers draining into Bangladesh Basin, *[8] Minor rivers draining into Myanmar Basin, *[9] Western Ghats.

Further, the NDVI, soil moisture, temperature and soil moisture data were regridded at a resolution of ($0.25^{\circ} \times 0.25^{\circ}$) using a nearest-neighbor assignment algorithm to match the consistency of high resolution precipitation data set. Considering seasonal variations are one of the key factors in vegetation-climate interactions, we incorporated both cropping seasons (Kharif: July–October and Rabi: October–March) and annual scale (January–December) in our study and separated the monthly values of each data set accordingly.

2.3. Copula based probabilistic model

Copula is a flexible approach to represent multivariate joint distribution (Nelson, 2006). Although, copula theory was tabled in the mid of 20th century by Sklar (1959), wide applicability of copula in different fields has come into picture only in recent years. A wide range of studies in hydrology (Salvadori and De Michele, 2015; Zhang et al., 2012), remote sensing (Das et al., 2018; Hedhli et al., 2017; Mercier et al., 2008), (Marti et al., 2016), finance (Bouyé et al., 2000; Ning, 2010) are available which have employed copula based approach for understanding the joint behavior of involved variables. Conventional bivariate approaches suffer from many limitations (Zhang, 2005) and have limited efficiency because of the constraints related to probabilistic distributions. It is difficult to incorporate other important aspects of time series such as stationarity and scaling properties in current bivariate models. However, copula based approach offers an alternative to overcome these limitations. For example, one can individually account for the marginal and joint distributions of random variables (Grimaldi and Serinaldi, 2006). The complexity of dependence can be modeled with the help of many existing copula families and their associated parameters. Briefly, according to Sklar's theorem (Sklar, 1959), a multivariate distribution $F(x_1, x_2 \dots x_n)$ can be expressed by a copula as:

$$F(x_1, x_2, \dots x_n) = C\,[F_{X_1}(x_1), F_{X_2}(x_2) \dots F_{X_n}(x_n)] = C\,(u_1, u_2 \dots u_n) \tag{1}$$

where, $F_{X_i}(x_i)$, denoted by u_i in the copula definition denotes the i^{th} variable, and C is the cumulative copula distribution function. Of the many existing copula families, copulas from the Elliptical family (Gaussian and t) carry several properties of the multivariate Gaussian distributions (Favre et al., 2004b). Archimedean copulas (Gumbel, Clayton and Frank) are another widely used copula class as they offer greater versatility modelling data with inconsistent dependencies. In this study, we have chosen Frank copula from the Archimedean copula families. Additionally, we have also used Plackett copula types to accommodate more flexibility in modelling joint behavior of our data. There are many advantages of selecting the mentioned copula types. Firstly, the density of Frank and Placket copula types offer great versatility to incorporate a variety of marginal processes (Chiou and Tsay, 2008). Secondly, parameter for these copula types used to quantify the association between different marginals is single in number, hence, the methodology involved to model the dependence structure of variables is relatively simpler and flexible (Ganguli and Reddy, 2014). Moreover, the copulas chosen in this study are capable of modelling a wide range of dependence including positively and negatively correlated variables, which may be the case considering the type of datasets used in this study (Zhang and Singh, 2007). It is necessary to find most suitable marginal probability distribution for each random variable before modelling their joint structure. For this purpose, six different probability distributions (Gaussian, Gamma, Lognormal, Weibull, Generalized Pareto and Generalized Extreme Value distributions) were compared based on their goodness-of-fit (Kolmogorov-Smirnov) statistics. After finding the best fit marginal distribution function for all the four variables on seasonal and annual scale, best fit copula function out of Plackett, Gaussian and Frank copula was decided by log likelihood approach (Gómez et al., 2017). Best copula and copula parameters for all the cases were found using Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) which estimate the relative performance of considered models (Cong and Brady, 2012; Lasmar and Berthoumieu, 2014). The chances of vegetation drought were estimated by analyzing the conditional probability of vegetation (NDVI) with respect to different in climatic condition (precipitation, temperature

and soil moisture content. Calculation of the conditional probability distribution, in such case, for a set of variables (NDVI-Precipitation, NDVI-Soil Moisture content and NDVI-Temperature) as $N_1 \le n_1$ and $N_2 \le n_2$ can be given as:

$$F_{N_1 \le n_1 | N_2 \le n_2}(n_1, n_2) = \frac{C(F_{n_1}(N_1), F_{n_2}(N_2))}{F_{n_2}(N_2)} = \frac{C(u_1, u_2)}{u_2} \tag{2}$$

This conditional probability distribution for NDVI was estimated in two different stressed scenarios of temperature, precipitation and soil moisture content. These two different scenarios represent the non-exceedance of the 20th and 60th percentiles ($n \le 20\%$and $n \le 60\,\%$) of the climate variables. To quantify the stress induced on vegetation, we have identified a threshold NDVI value corresponding to less than 30th percentile ($n_{NDVI_{drought}} \le 30\,\%$) as an indicator of vegetation drought. The conditional probabilities were calculated for each season and annual scale for all the grid points across the country.

2.4. Quantification of resilience

As discussed, resilience is one of the widely used approaches for describing the response of ecosystem to climate disturbances. Because of expected rise in such disturbances and its implications on the vegetation cover, it has become important to understand the capacity of different ecosystems to fight against these disturbances. During a drought event, reduction in soil moisture content affects the growth of plant species. One of the most widely used tools for identifying and monitoring droughts all over the world has been Standard Precipitation Index (SPI) which incorporates the information about drought history at a particular point (Buttafuoco et al., 2015; Radzka, 2015; Zarch et al., 2015). To estimate the impact of droughts on vegetation ecosystems in from resilience point of view, we first identified the driest year during the period of 1982–2010 based on long term climate data by deriving the Standardized Precipitation Index (SPI) (Mckee et al., 1993; Vicente-Serrano et al., 2010). Since we have considered the case of vegetation related droughts, we expect that a resilient ecosystem will recover quickly against a dry condition and maintain its vegetation vigor. The vegetation distribution at a particular point, which showed relatively undisturbed NDVI value in driest year ($\mathrm{NDVI_d}$) is considered as resilient. Most of the resilience studies suggest that for a fully resilient ecosystem the ratio of disturbed to a given baseline state approaches to 1, indicating complete recovery (Ingrisch and Bahn, 2018). We define an index, $\mathbf{R_i}$ to measure resilience as a ratio of NDVI in the driest year to its temporal mean ($\mathrm{NDVI_m}$) value calculated over the period of 1982–2010 Eq. (3).

$$R_i = \frac{NDVI_d}{NDVI_m} \tag{3}$$

3. Results

3.1. Temporal variability of NDVI, precipitation, temperature and SMC

Before proceeding to the probabilistic modelling of vegetation drought, we investigated the temporal variability of NDVI, precipitation, temperature and soil moisture content. Trend analysis of the parameters for the period of 1982–2010 was performed on both seasonal and annual scale separately using non-parametric Mann Kendall (MK) test with 5% significance level. The results were classified into three different categories based on the value of Z statistics which are: significantly increasing (+S) for Z greater or equal to 1.96, significantly decreasing (-S) for Z less than −1.96 and non-significant trend for the values in between. For relative comparison, the MK test results of NDVI were clubbed together with each one of the climate variables forming 9 different combinations as shown in the legend of Fig. 2. Separate analysis was done for annual (Fig. 2a), Rabi (Fig. 2b) and Kharif season (Fig. 2c) scale. Overall NDVI trends suggest that vegetation has significantly increased in most parts of the country. Non-significant trends were captured in the Himalayan and north-western part. The trends of NDVI remained almost similar on seasonal and annual scales. Precipitation trends turned out to be mostly non-significant on both annual and seasonal scales except in Rabi season where some major regions in northern India are witnessing decreasing trends. There was no significant spatial pattern in trends of temperature. Some parts of the country (north east and upper Himalayas) showed significantly increasing temperature trends along with increasing NDVI while most of the central and southern regions depicted non-significant trends. Similarly, soil moisture content trends suggest no particular increase or decrease in most parts of the country irrespective of time scale. The climate variables majorly show non-significant trends on seasonal as well as annual time scales and the influence of climate conditions on vegetation is unclear from the trend analysis. This random variability of climate variables makes it difficult to interpret the dependence of NDVI over climate. Hence, the trend analysis results suggest that more efficient method is needed to understand the vegetation climate dynamics of the country.

3.2. Vegetation drought likelihood

The joint distribution of NDVI-temperature, NDVI-precipitation and NDVI-soil moisture content were estimated on both seasonal and annual scales. Once, the joint probabilities were obtained, the conditional probability of NDVI value with threshold ($n_{NDVI_{drought}} \le 30\%$), which represents a vegetation drought condition was evaluated using Eq. (2) at each grid point in two different scenarios ($n \le 20\%$and $n \le 60\,\%$). The results for first scenario ($n \le 20\,\%$) is shown in Fig. 3 (see Fig. S1 for second scenario i.e.$n \le 60\%$). We classified the conditional probability values to define the vegetation drought risks as extreme (0.75–1), high (0.50–0.75), moderate (0.25–0.50) and low (0.25–0.00). On annual scale, most of the basins in the country except some in North East region (e.g. Barak) were susceptible to moderate or high vegetation drought. High likelihood of vegetation droughts was observed in NDVI-soil moisture content analysis which indicates that soil moisture deficit is the biggest threat to existing vegetation cover (Fig. 3c). Significant areas of river basins like Pennar, Krishna, Mahi, Sabarmati and Luni showed high or extreme likelihood of vegetation drought when lower precipitation scenario ($n \le 20\%$) was considered. However, lower soil moisture conditions($n \le 20\%$) worsens the situation and the extent of areas under high drought likelihood further increases (Table 1). Lowering the soil moisture, temperature and precipitation is necessary to understand the impact of extreme changes in climate scenario on vegetation cover of the country. A significant change in the vegetation cover with threshold ($n_{NDVI_{drought}} \le 30\%$), gives the quantification of vegetation drought risks conditioned on a given climate scenario ($n \le 20\,\%\, and \le 60\%$) which has also been utilized in a significant study of vegetation-climate interaction across China (Liu et al., 2016b).

This indicates that these river basins are unable to hold the incident precipitation for a longer duration to ensure enough soil moisture for their vegetation. Although, a significant percent of the above mentioned river basins are facing high risks, but it is important to note that even smaller percentage (7.03%) in large river basins like Ganga accounts for huge area of 56,089.53 km^2 which also needs to be addressed. On seasonal scale, higher risks were observed in Rabi season than Kharif season which is shown in Fig. 4(a–c). The river basins in the north east region were least susceptible to vegetation droughts in lowered precipitation and soil moisture conditions. However, lower temperature scenarios do induce some risks in these areas. This may have caused due to the lack of necessary warmth or sunshine for plant growth in cold regions (see NDVI-temperature plot in Fig. 3). Hence, increase in temperature in these regions may lower the vegetation drought risks. Moreover, low temperature scenarios do not have any significant impact on most of the other river basins which is obvious. Detailed results at seasonal scales for all river basins have been

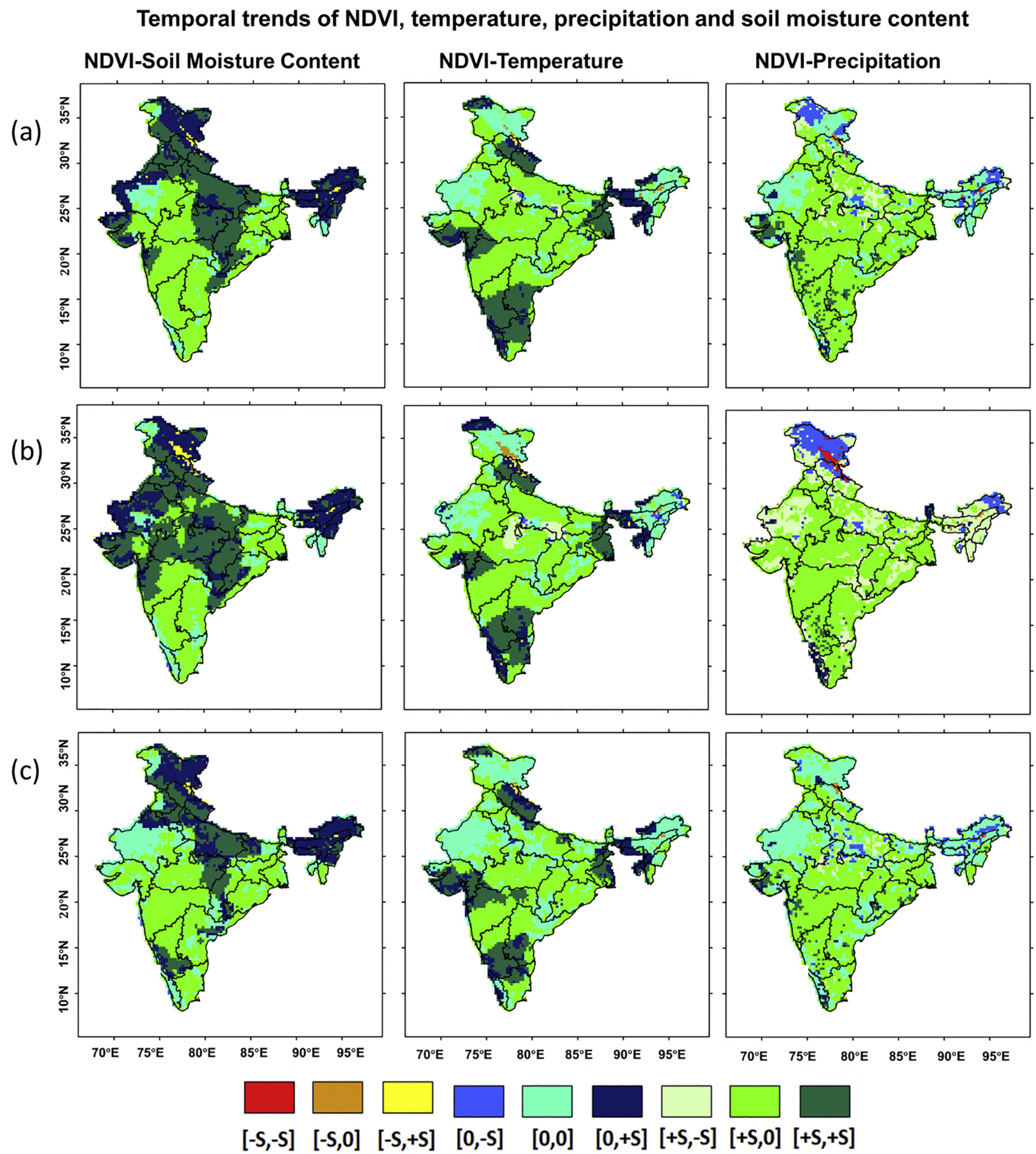

Fig. 2. Trends analysis results at (a) Annual (b) Rabi and (b) Kharif seasonal scale. First and second letters in the color code represent trend of NDVI and one of the three climate variables respectively. +S, −S and 0 represent significantly increasing, significantly decreasing and non-significant trends respectively.

Included in the supplementary information which may be referred for more information.

Most dominant land cover type in the country is cropland, which majorly contributes to the agricultural production. Soil moisture content remains the most significant factor affecting the croplands (Table 2). Further, lowered precipitation scenario augments the chances of vegetation drought more severely than lowered temperature scenario. While lowered precipitation has negligible impact on evergreen forests and deciduous forests types, role of temperature is significant in these forest types and lowering the temperature profile increases the chances of drought (Fig. 5). On seasonal scales, as obtained in the study at river basins scale, extreme or high drought risks are more evident in the Rabi season. A total area of 7, 88,705 km^2 of the cropland fall under high or extreme drought risks in Rabi season in low

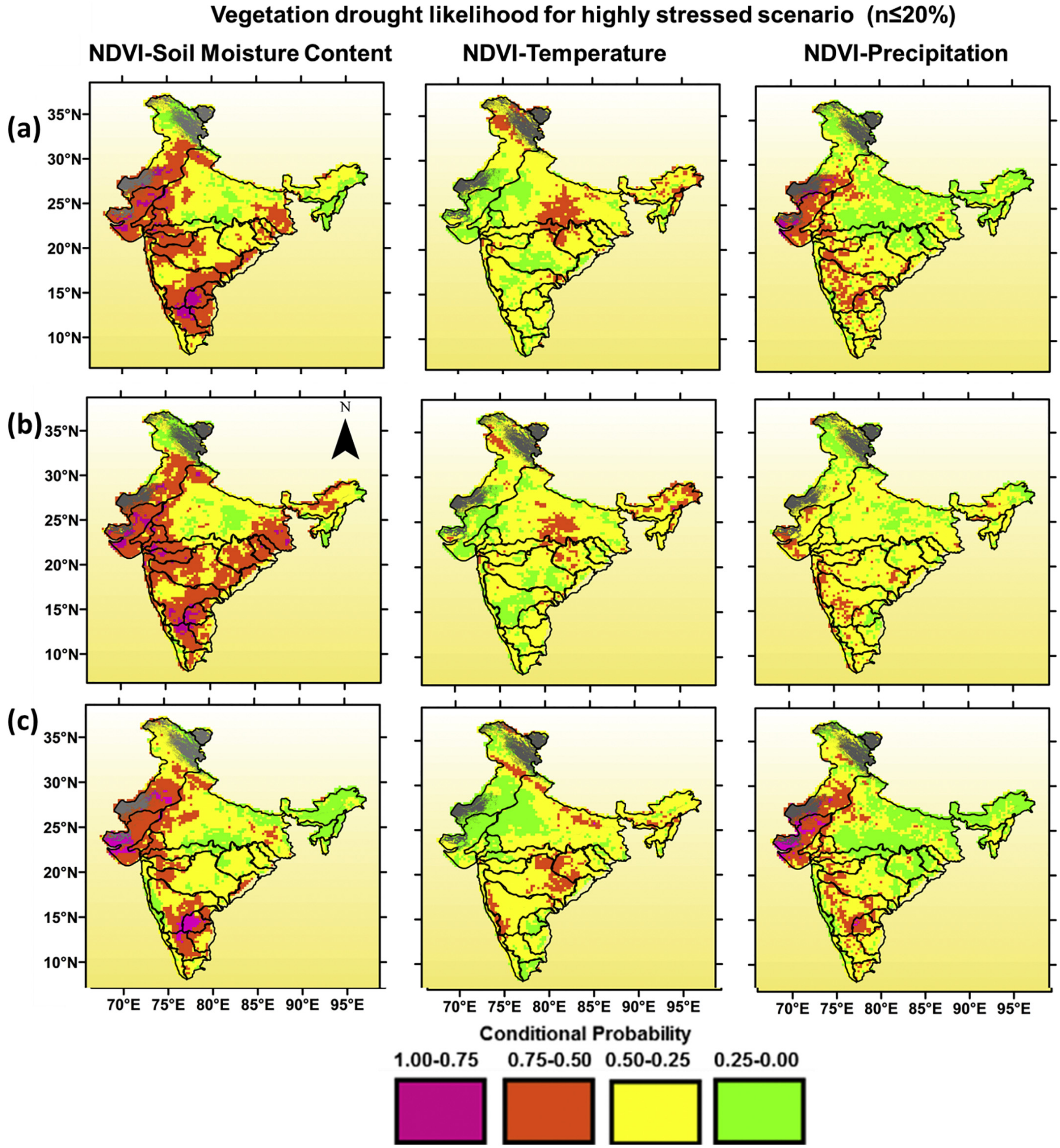

Fig. 3. Vegetation drought probabilities for (a) Annual (b) Rabi and (c) Kharif scale for all the three combinations of NDVI-Soil Moisture Content, NDVI-Temperature and NDVI-Precipitation cases in for highly stressed climate scenario (n ≤ 20%).

soil moisture scenario (Table S2). Evergreen forest is almost undisturbed in Kharif season and remains safe from drought risks probably because of improved water availability in the monsoon months. However, about 33% and 39% of cropland and cropland/natural vegetation mosaic respectively fall under high or extreme vegetation drought risks in the same season, raising serious concerns about India's food security (Table S4).

3.3. Resilience of river basins and different vegetation types

Fig. 6 represents the resilience values obtained by Eq. (3) across India. The maximum and minimum value of $\mathbf{R_i}$ were 1.41 and 0.29 respectively. River basins in the arid zones of India such as Mahi, Sabarmati, Luni and EFRKPB were detected to be severely non-resilient (Fig. 7). Not only arid zones, the river basins which are known to be lifeline of Indian agricultural systems were also found to be highly

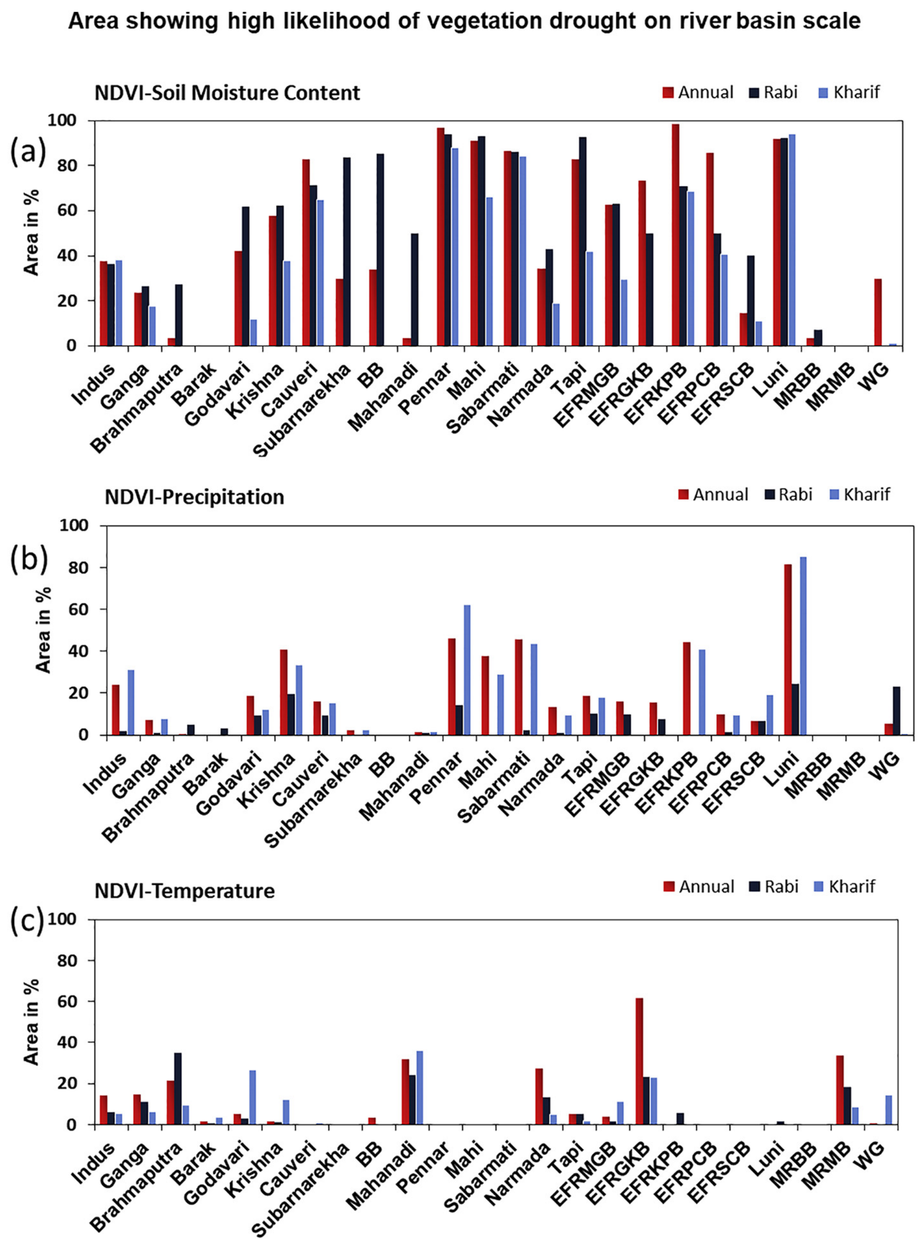

Fig. 4. Percent areas of river basins showing high likelihood of vegetation drought for (a) NDVI-Soil Moisture Content, (b) NDVI-Precipitation and (c) NDVI-Temperature cases in highly stressed climate scenario (n ≤ 20%).

Table 2
Area highly likely to be affected by vegetation drought on annual scale in stressed climate scenario (n ≤ 20%) for different vegetation types obtained from different sets of NDVI and climate variables.

Class	NDVI-Soil moisture content		NDVI-precipitation		NDVI-temperature	
	Area (%)	Area (km^2)	Area (%)	Area (km^2)	Area (%)	Area (km^2)
ENF	21.43	1986.66	0.00	0.00	35.71	3311.10
EBF	1.96	1986.66	0.65	662.22	13.73	13,906.63
DNF	9.38	1986.66	0.00	0.00	25.00	5297.76
DBF	7.41	2648.88	0.00	0.00	24.07	8608.87
MF	21.99	20,528.84	1.42	1324.44	17.02	15,893.29
WS	31.27	80,128.69	9.04	23,177.72	12.40	31,786.59
SAV	40.45	23,839.94	16.85	9933.31	21.35	12,582.19
GL	22.65	27,151.04	8.84	10,595.53	23.76	28,475.49
CL	44.78	686,722.75	22.24	341,043.60	9.84	150,986.29
CNV	56.76	125,159.69	18.02	39,733.24	6.61	14,568.85

vulnerable in dry conditions. Area-wise, Ganga and Indus river basins were observed to be most non-resilient ones. Both of these river basins have a significant fraction of land under agricultural use and a large population is dependent on them. The results clearly indicate that crop production in these river basins may not be able to sustain the vegetation droughts. Large river basins of southern India also face similar risks. Krishna and Godavari were most fragile river basins in the southern part of the country. Both the river basins are highly stressed in terms of water availability and non-resilient vegetation distribution increases the chances of putting their terrestrial ecosystem at risk. Investigation of the resilience on different vegetation scale indicates that more than half of all vegetation types are non-resilient to vegetation droughts. India has highest net cropland area in the whole world, which makes up > 50% of the country. The huge extent of non-resilient cropland aggravates the challenges to Indian agriculture. Furthermore, about 74% of MF (Mixed forests) and 72% of SAV (Savanna) type vegetation cover was non-resilient (Fig. 7). Mixed forest ecosystems which comprise of both coniferous and deciduous forest types were also

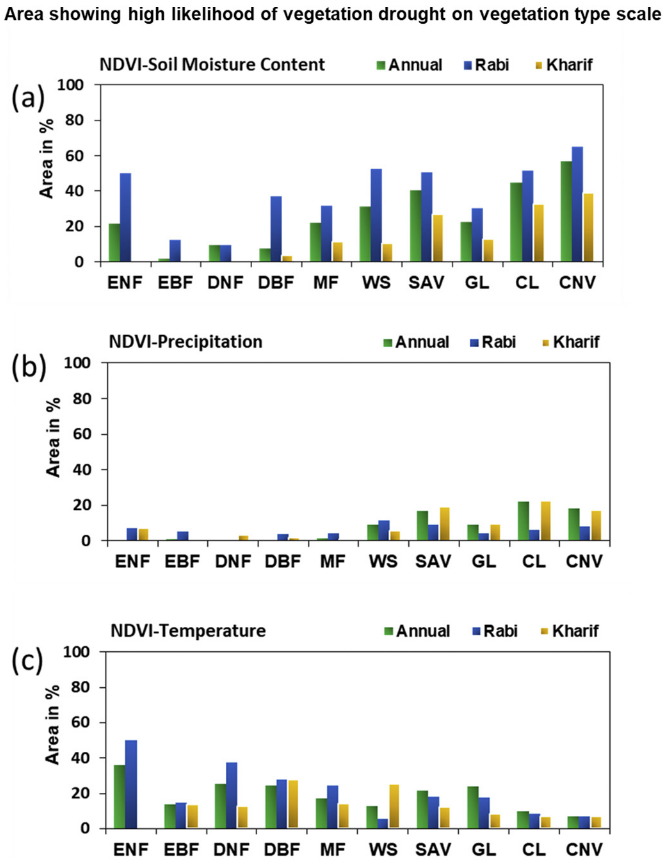

Fig. 5. Percent areas of land cover types showing high likelihood of vegetation drought for (a) NDVI-Soil Moisture Content, (b) NDVI-Temperature and (c) NDVI-Precipitation cases in highly stressed climate scenario (n ≤ 20%).

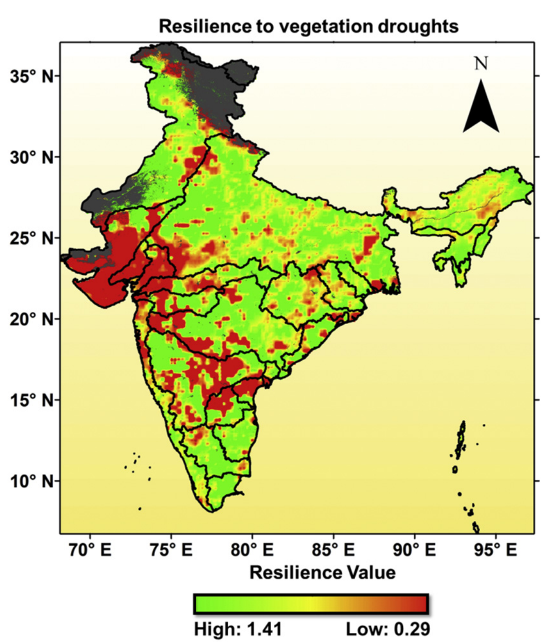

Fig. 6. Spatial distribution of resilience (R_i) values.

observed to be highly insecure against drought conditions. These forests are found in regions with a distinct cool and warm season which sums up to a relatively moderate annual temperature. In India, these are majorly distributed in the Himalayan range along with other forest types and it is alarming to see that even forest covers of these ecologically favorable zones are not safe from dry conditions. Deciduous forests are most widespread forests of India and are heavily dependent on monsoons. The distribution of these forests is based on the dry and moist conditions. We found that a possible dry condition is capable of altering > 65% of deciduous vegetation of the country. It is surprising that irrespective of its type, more than half of every vegetation cover is non-resilient. Hence, a possible vegetation drought scenario is expected to impact all vegetation types which a clear indicator of the threatened status of Indian vegetation ecosystem. The evergreen forests, which are found in high precipitation zones in the country such as North East and Western Ghats, were expected to be least affected by such disturbances. Unlike the deciduous forests, they do not shed their leaves all together during any part of the year. But, we found that both evergreen needle leaf and evergreen broad leaf forests were unable to recover from the driest conditions and 50–60% of the total area of the forest showed non-resilient behavior in their respective driest years in the period of 1982–2010 (Table S6). The non-resilience of such forest ecosystems means that even the greenest forest covers in the country are not stable against drought disturbances.

4. Discussion and conclusions

Despite increasing concerns over the growing challenges to terrestrial ecosystems, vegetation drought risks and their resilience to different climate conditions is least addressed at pan-India scale. We found that vegetation is significantly increasing in most of the regions in north-central and southern India. Precipitation trends were non-significant except some decreasing patterns in parts of north central and north eastern India. Temperature was reported to be significantly increasing in some regions in northern India. Similar was the case of soil moisture content which also exhibited some arbitrary patches of increasing trends. Simple trend analysis climate variables and NDVI do not suggest any significant correlation between them highlighting the complex vegetation-climate dynamics of the country. Variability of climate factors has significant implications for vegetation in India (Sarkar and Kafatos, 2004). This encouraged us to look for more efficient approaches to understand the vegetation-climate interaction. To estimate the vegetation drought risks, we used a copula-based multivariate probabilistic estimation model to characterize different areas of India based on high and extreme vegetation drought risks. In lowered soil moisture condition, Mahi, Luni and Sabarmati river basins of the North Western parts of the country showed very high likelihood of vegetation droughts. Dhorde and Patel (2016) have suggested that majority of these regions have chances of increased drought intensity. Arid regions of Southern India were also found to be highly susceptible to drought conditions. > 96% area of Pennar river basin was likely to suffer from vegetation droughts in a reduced soil moisture condition (Table 1). Other major river basins in the region such as Cauveri, Tapi and Krishna were also unsafe from the drought risks and > 50% of their areas were vulnerable. In India, the extent of soil moisture droughts is projected to increase in the near future (Mishra et al., 2014). This indicates that the vegetation ecosystems across the country are likely to see more threatening circumstances in the near future. However, low drought likelihood in Brahmaputra, Barak and its nearby basins suggests that vegetation cover in these regions can sustain extreme changes in soil moisture profiles. Assessment of lowered precipitation levels showed that Luni river basin was the most vulnerable with 81% of its area (1, 50,691 km^2) falling in high risk zone which is supported by the fact that this river basin receives the minimum mean annual rainfall (Jain and Kumar, 2012). Further stressing of precipitation profile is fatal for vegetation cover in the region. Regions in the country such as North East, Western Ghats and some parts of the East Coast exhibited low likelihood of vegetation droughts. Minor areas of Brahmaputra, Barak, and Mahanadi river basins were at the risk of losing their vegetation cover in lowered precipitation condition indicating that the regions receive ample rainfall avoid vegetation drought risks. It is

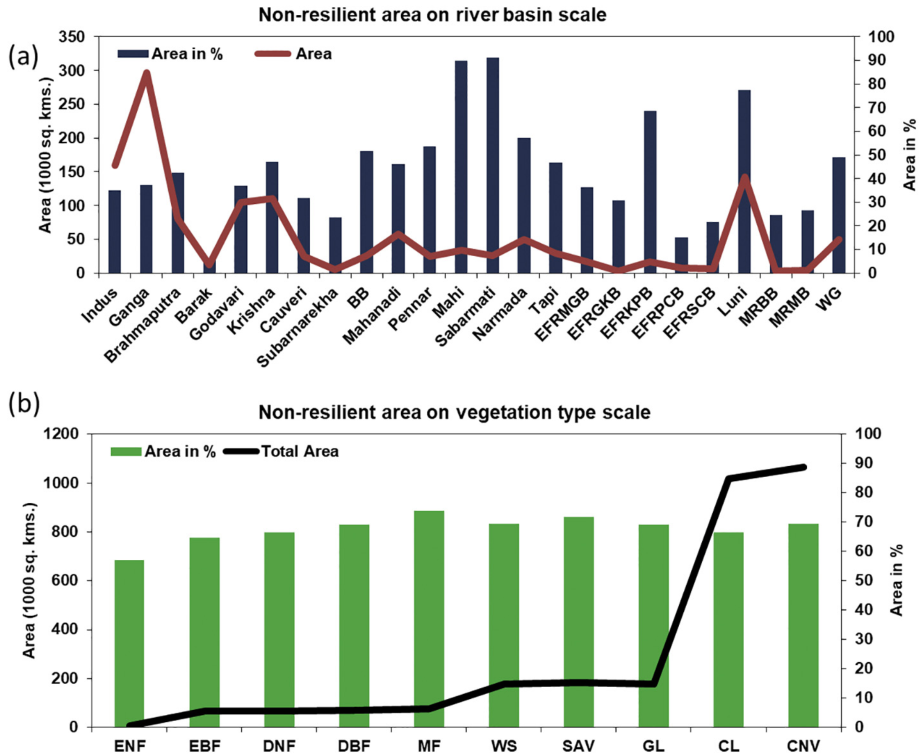

Fig. 7. Non-resilient area at (a) river basins and (b) vegetation types scales.

important to mention that the effect of lowered soil moisture condition is more severe than lowered precipitation. For example, Ganga river basin receives an average of about 1000 mm of rainfall annually (Quincey, 2017). With lowered precipitation scenario, about 7% (56,089 km^2) of the river basin area was lying under high drought risks, whereas, a lowered soil moisture scenario converts > 23% (186,076 km^2) of the river basin into high risk zones (Table 1). It is also interesting to note that the river basins which were highly likely to suffer from drought risks due to lower soil moisture levels like Luni, Tapi, Mahi and Pennar were safe in lowered temperature scenario. This means that lesser temperature in the river basins of the north-west and south India favors the vegetation ecosystem in these regions. However, this tendency is somewhat altered in the Himalayan regions where lowering the temperature causes high likelihood of droughts. The cold arid climate in these mountainous regions is not supportive of vegetation growth and further lowering the temperature affirms this fact. The link between climate variables and vegetation is highly dependent on seasonal variability (Kong et al., 2017) hence, it was important to examine the seasonal dependence of NDVI with the climate variables. Vegetation in Rabi season was more vulnerable to extreme climate conditions and more than half the area of 16 out of 24 river basins showed high likelihood of drought (Table S1). Area wise, most badly affected river basin was Ganga, of which 211,364 km^2 (26%) was prone to vegetation droughts. Soil moisture deficit in the Rabi season indicates poor availability of irrigation water to sustain crop growth in the river basin and points out the dependence on monsoon rains. It is also evident from the result in Kharif season in which the vegetation drought prone area reduced to 142,884 km^2 (18%) (Table S2). The seasonal dependence can also be observed in the response of different vegetation types. We found that evergreen needle leaf, evergreen broadleaf and deciduous needle leaf forest were almost safe from vegetation drought risks in Kharif season. Whereas, lowered soil moisture levels in Rabi season increases vegetation drought risks in half of evergreen needle leaf forest areas. Readers are advised to refer supplementary information for more detailed account of vegetation response to relatively higher level of precipitation, temperature and soil moisture content ($n \leq 60\%$) (Fig. S1).

Ecosystem productivity is affected by extreme hydro-climatic conditions and response of different vegetation types to such conditions is explicit and depends on several factors. It was clear from the vegetation drought part of our study that water availability primarily controls the vegetation ecosystems both on seasonal and annual scales. We investigated the behavior of vegetation in during the time period of least water availability with the help of SPI which is correlated to NDVI (Ji and Peters, 2003). Resilience was estimated in terms of ability of an ecosystem to maintain its NDVI (vegetation vigor) in the driest year as compared to the mean NDVI during the time period 1982–2010. Our study shows that none of the river basins is resilient to vegetation droughts and at least one-third area of 18 out of 24 river basins is fragile against such disturbances (Table S3). Moreover, at least three-fourth areas of river basins situated in the arid zones in the country such as Mahi, Luni, and Sabarmati were found to be non-resilient. These river basins already have scarce vegetation distribution and are highly prone to vegetation droughts. The non-resilience of such river basins essentially points towards their inability to achieve the essential moisture condition for vegetation regrowth after a dry period. A vegetation drought event in such basins is likely to last longer as compared to others. Barak river basin, which lies in India's one of the most ecologically rich regions was most efficient in supporting its vegetation cover in a relatively dry year. Further, we also examined the ecosystem resilience based on the land cover scale to check the capability of different vegetation types to recover from drought condition. Area-wise, evergreen needle leaf and evergreen broadleaf forests were most resilient vegetation types. However, our analysis showed that more than half of every single vegetation type in the country was incapable of fighting dry conditions (Table S4).

India has an agriculture-based economy and a huge amount of population depend on agricultural activities for their livelihood, hence, high risk of vegetation drought is alarming for the country. Croplands are most dominant land cover in the country and our analysis shows that a huge area of 10,19,157km^2 (66%) of the total croplands is vulnerable to vegetation drought, which needs immediate attention. Rice

producing regions in the Eastern coastal plains along with areas in the Ganga and Indus river basins were found to be highly vulnerable on Annual scale (Fig. 1). Whereas, soil moisture deficit in the Rabi season can pose serious threat to major wheat producing river basins such as Indus, western parts of Ganga basin, and productive regions of Sabarmati, Mahi and Luni river basins. Apart from some parts of Indus river basins (Punjab and Haryana states), most of these regions are lack sufficient infrastructure for irrigation facilities despite several integrated water management efforts (Bokil, 2000; Pathak et al., 2013; Sharma and Sharma, 2006). Since, these areas receive less than normal rainfall, it is understandable that ensuring sufficient moisture for supporting Rabi crops in this region is always difficult. As obtained in the resilience analysis, most of the river basins, which were highly non-resilient (Pennar, Sabarmati, Luni, Mahi) were also highly susceptible to vegetation droughts. Similarly, Barak river basin, which was the least vulnerable, was also found to be most resilient in dry conditions. Hence, a vegetation drought event in arid basins is expected to last longer as compared to moderate or good precipitating regions which adds further concerns to the agricultural activities.

Hence, we concluded that there is a significant threat to the vegetation cover of the India, especially in the western and southern most parts. Large areas of most river basins are susceptible to high chances of vegetation drought due to possible deficit of required soil moisture levels. Further analysis of resilience shows that most of the river basins are incapable of recovering from a vegetation drought condition. This implies that a vegetation drought condition in India may affect the terrestrial ecosystem productivity for a long period of time and can cause large scale damage to the ecosystem services. More importantly, this trend was observed irrespective of vegetation types. More than half area of every land cover type exhibited non-resilience. A similar threat was observed even for rich forest type such as evergreen forests which are supposed to be resilient to a dry condition. We also covered the seasonal aspects of the vegetation response and found that Kharif season was relatively more favorable for vegetation growth and activity. However, the NDVI data is only available after 1982, the dynamic annual or seasonal changes in vegetation cover against climatic conditions over longer time scale could not be estimated and compared. Despite the relatively limited availability of data, the proposed approach performs reasonably well. The vegetation-related drought risks were analyzed under the assumptions of stationarity and scale independence incorporating which would allow more comprehensive and detailed investigation of the involved mechanism. Moreover, this study aims at identifying the bivariate dependence structure of climate variables and vegetation patterns which may not be sufficient in incorporating complex ecosystem-climate interactions. Hence, instead of using bivariate, a trivariate copula approach may be utilized in future studies considering the interrelationship of more than climate or vegetation parameters. Further, the physical climatological mechanisms determining climate variability and the impacts related to the large-scale climate drivers are not considered in the present analysis which may be explored in future studies.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gloplacha.2019.01.014.

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